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# The Path Length Prediction of MANET using Moving Average model

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**Abstract**

Wireless networks are organized as a network with mobile nodes that act as hosts and routers to broadcast packets. The frequent changes of network topology, the path length between source and destination nodes also varies for changing of time. The path length happens to be a very important parameters for QOS routing. Predicting the path length from a source to a destination in ad hoc networks may help in several network functioning. The path length between a source destination pair depends on the mobility patterns as well as routing algorithms. In this article, We have considered the path length from a source node to destination node as a random variable and tried to predict them using the concepts of Moving average model of order $q$ i.e. MA($q$) of time series analysis. We also calculated the average path length and the performance of each mobility models with the routing algorithms.


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*Keywords:* ad hoc network, path length, mobility models, Time series analysis, routing model, moving average

## 1. Introduction

Wireless ad hoc networks are emerging networks for many important applications such as military battlefield communication, mobile classrooms, disaster management, environmental monitoring, traffic control etc. Path length prediction in the future time frame focuses on characterizing how well a path can be predicted between two mobile nodes. If two nodes are present within their transmission range then direct communication may happen between them. Otherwise, source node creates path using several number of intermediate nodes or hops to reach the destination[1, 2]. The mobility models can describe the movement pattern of mobile nodes and explain, how their velocity, location and movement change over time. These may play a significant role to determine the protocol performance. Here we considered three common mobility models like, (*i*) Manhattan Grid mobility(MHG), (*ii*) Reference Point Group Mobility Model (RPGM), and (*iii*) Gauss Markov mobility(GMK). Camp et. al. [3] provided a good survey on the

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most frequently used mobility models. The multi-hop routing is a common attribute in MANETs. In this paper, the Adhoc On-demand Distance vector (AODV) and Dynamic Source Routing (DSR) protocols are considered which are both of reactive routing protocols in nature. Moving Average(MA($q$)) models provide a sparing description of a stationary stochastic process in terms of a polynomial. So, we may apply MA($q$) technique for forecasting the path length between source and destination node of mobile nodes.
The Impact of Mobility on the Performance Of RouTing protocols in Adhoc NeTworks(IMPORTANT) is a popular framework proposed by Bai et al.[4] which describes the relationship between the routing protocols and different mobility patterns. They also generated of some useful metrics such as degree of spatial dependence, degree of temporal dependence, connectivity graph, link duration etc in MANET. M. Abolhasan et al.[5] projected a review of different routing protocols in MANET. [6, 7] proposed the details of time series modelling for forecasting. Singh et. al. [8] showed the distribution of neighbour count of a node under a threshold value of speed, range and sampling time can be correlated and it may be represented by $AR(p)$ model for suitable choice of $p$. In other article [9], they modeled the link load distribution between two nodes using a $AR(p)$ model and predicated the link loads in future time frames and established that the prediction is close enough to actual value. In [10], Singh et. al. compared through different routing protocols according to their path lengths and established that DSDV achieves the shortest path length across all mobility models. They modeled the path length distribution between two nodes using a Auto-regressive $AR(p)$ model and found that path length distribution between two nodes under all mobility models are well correlated and can be represented by $AR(p)$ model for suitable value of $p$. The rest of this paper is organized as follows. We describe our approach in section 2. Performance evaluation is provided in section 3 and in section 4, we discuss the results. We conclude the article in section 5 with some indications regarding future directions.

## 2. Our Approach

In this paper, we try to predict the path length $P^{ij}$ between a pair of mobile nodes $N_i$ and $N_j$ in MANET using Moving Average MA($q$). In this article, we have proposed a model with MA($q$) for prediction of path lengths where $q$ represents the order of the MA($q$). The order $q$ of the MA($q$) is also evaluated as the exact choice of the time lags is the crucial factor for a good forecasting performance[11].

For instance, a time series process $y_t$ of a first order moving average $MA(1)$, can be expressed as

$$y_t = \mu - \theta_1 \varepsilon_{t-1} + \varepsilon_t \tag{1}$$

and the $q$ order of MA(q) can be defined as

$$y_t = \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} \tag{2}$$

where $\varepsilon_t$ are independently and identically distributed Gaussian white noise with zero mean and constant variance $\sigma^2$ for $t = 1, 2, ..., n$.

In MA model, the autocorrelation function (ACF) and partial ACF (PACF) are very important metrics to analyze the internal structure of the time series. The $ACF_\rho(k)$ at lag $k$ of the series $y_t$, is the linear correlation coefficient between $y_t$ and $y_{t-k}$, for $k$ =0, 1, 2...
So, the autocorrelation at lag $k$ is

$$\rho_k = \frac{\sum\limits_{t=1}^{n-k} (y_t - \overline{y})(y_{t+k} - \overline{y})}{\sum\limits_{t=1}^{n} (y_t - \overline{y})^2} \tag{3}$$

where $\overline{y}$ is the mean value.

The order of $q$ of MA($q$) are determined using Akaike Information criterion (AIC). The proposed network is using AODV and DSR protocols and it is simulated for three different mobility patterns namely : ($i$) Manhattan Grid (MHG), ($ii$) Reference Point Group mobility model (RPGM) and ($iii$) Gauss-Markov mobility model. For these protocols and for each simulation setting, we calculate the path length under a specific mobility scenario varying for different routing protocols. We have taken total 200 data set for each routing protocols and mobility models of our

Table 1. Simulation setup

| | |
|---|---|
| Simulator | NS-2 |
| Routing protocols | AODV, DSR |
| Scenario dimension | 1000m x 1000m |
| Simulation time | 1000s |
| Number of nodes | 30 |

experiment for MA($q$) model. According to the above considerations, the detailed steps of the proposed method can be described as follows:
*Phase I (Determine the order of MA model)*: Consider the lowest AIC value of MA($q$) to choose the order of $q$.
*Phase II (Determine the correlation function)*: According to the suitable order of MA($q$), we found the amount of variation and correlation for the path length under a specific mobility model with different routing protocol and predict the future path length values for each mobility models.
*Phase III (Performance evaluation and comparison)*: Calculate the performance and compare it with different routing protocols and calculate the average path length.

## 3. Performance Evaluation

Different metrics like Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error(MAPE) are used for these purpose of evaluation. The formula to calculate these performance evaluation criterion are offered below from equation 4 through 6. Here $O_i$ and $P_i$ are the actual and forecast path lengths respectively between mobile nodes for $i$−th time respectively. $\overline{O}$ and $\overline{P}$ are the mean values of actual and forecast path lengths. $N$ is the total number of sample values.

Root mean squared error (RMSE):

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(O_i - P_i)^2} \tag{4}$$

RMSE defines the inconsistency between the actual and predicted values.
Mean Absolute Error (MAE):

$$MAE = \frac{1}{n}\sum_{i=1}^{N}(|O_i - P_i|) \tag{5}$$

MAE calculates the error of prediction by measuring the deviation between actual and forecast value.
Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{100}{n}\sum_{i=1}^{N}(|\frac{O_i - P_i}{O_i}|) \tag{6}$$

## 4. Results and discussion

We test our model using NS-2 [12] for network simulation and traces are generated in new trace format. BonnMotion is a Java based simulation software that creates and analyses mobility scenarios. The generated scenarios are then exported to NS-2. Simulation parameters are shown in Table 1. To determine the order $q$ of MA, we calculated Akaike Information Criterion(AIC) values of different orders and choose the minimum AIC.

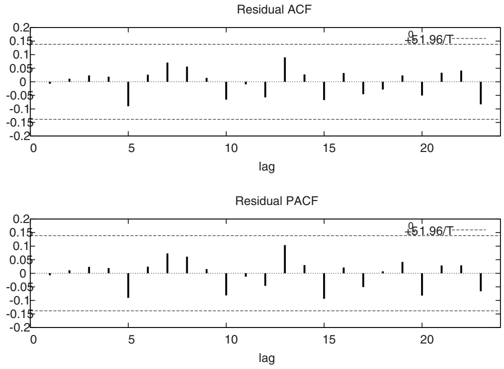


Fig. 1. Autocorrelation function (ACF) and Partial autocorrelation functions (PACF) of path length values for AODV routing protocol using MHG Mobility pattern

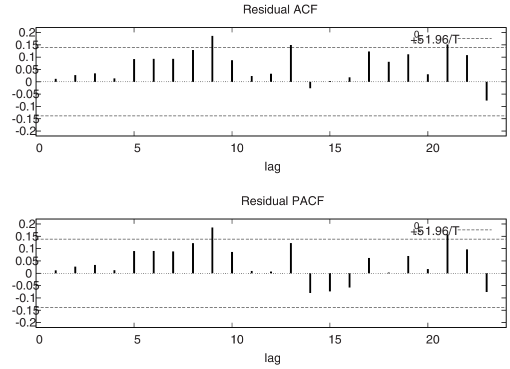


Fig. 2. Autocorrelation function (ACF) and Partial autocorrelation functions (PACF) of path length values for DSR routing protocol using MHG Mobility pattern

Table 2. The AIC values of different $MA(q)$ models in AODV routing and MHG mobility model

| $MA(q)$ | AIC |
|---|---|
| (1) | 739.2081 |
| (2) | 740.8175 |
| (3) | 737.5761 |
| **(4)** | **734.1822** |
| (5) | 736.1084 |

Table 3. The AIC values of different $MA(p, q)$ models in DSR routing and MHG mobility model

| $MA(q)$ | AIC |
|---|---|
| (1) | 753.1235 |
| (2) | 754.4942 |
| (3) | 749.2252 |
| **(4)** | **745.0176** |
| (5) | 745.4354 |

Table 4. Performance Comparison between different routing protocols using MHG mobility model

| | Average actual path length | Average predicted path length | Root Mean Squared Error(RMSE) | Mean Absolute Error( MAE) | Mean Absolute % Error(MAPE) |
|---|---|---|---|---|---|
| AODV | 3.86 | 4.65 | 1.2648 | 1.0877 | 34.72 |
| DSR | 2.96 | 2.3 | 1.3863 | 1.1721 | 61.75 |

### *4.1. Analysis the path length on MHG mobility model*

The AIC values for different orders $q$ of MA for MHG mobility model with AODV and DSR routing are shown in Tables 2 and 3 respectively. The bold faced values in these Tables indicate best performing order of MA model for the respective path length series. It can be seen from Tables 2 and 3 that $4^{th}$ order of MA model is giving the best fit for these data sets. The auto correlation function(ACF) and partial auto correlation function(PACF) are shown in the Figures 1 and 2. The predicted path lengths and the actual path lengths of different routing protocols for MHG mobility model are shown in Figures 3 and 4. Comparison between average actual path length and average forecast path length is in the Figure 5. Performance analysis of the path length prediction with a specific mobility model is calculated in the Table 4. One can observe that AODV routing has the lowest RMSE, MAE and MAPE as can be seen from Table 4.

### *4.2. Analysis of the path length on RPGM model*

The AIC values for different orders $q$ of MA($q$) for path length moving under RPGM model and following AODV and DSR routing protocols are tabulated in the Tables 5 and 6. The bold face point out the best performance. The order of MA is found to be 5 here as evidents form Tables 5 and 6. The Fig. 6 and 7 depicts the ACF and PACF graphs for AODV and DSR protocols respectivly. The forecasted path lengths of mobile nodes in AODV and DSR

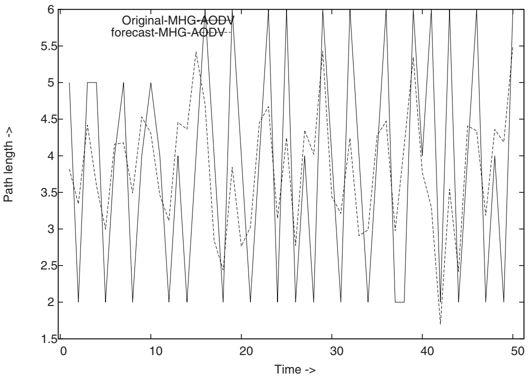


Fig. 3. Time series plot of path length for AODV routing protocol using MHG Mobility pattern

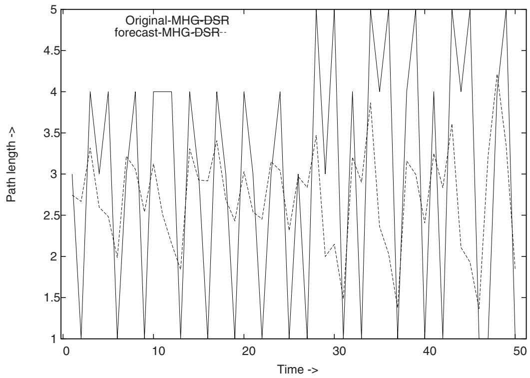


Fig. 4. Time series plot of path length for DSR protocol using MHG Mobility pattern

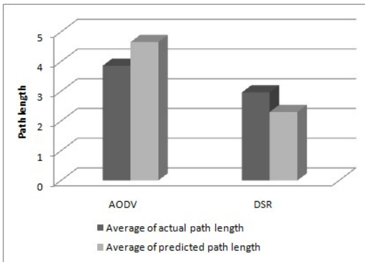


Fig. 5. Comparison between the actual path length and predicted path length of different routing protocols in MHG Mobility pattern

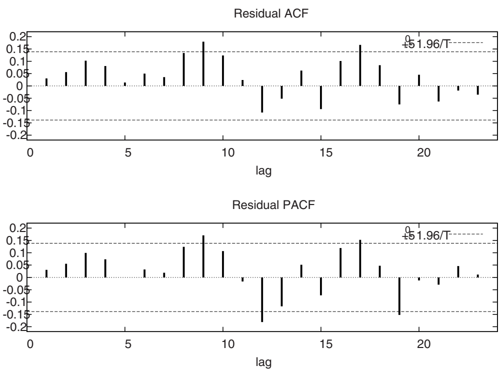


Fig. 6. Autocorrelation function (ACF) and Partial autocorrelation functions (PACF) of path length values for AODV routing protocol using RPGM Mobility pattern

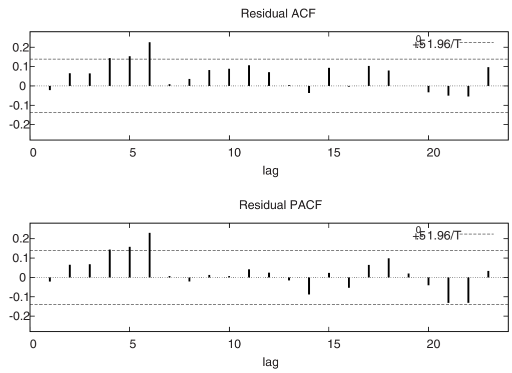


Fig. 7. Autocorrelation function (ACF) and Partial autocorrelation functions (PACF) of path length values for DSR routing protocol using RPGM Mobility pattern

are plotted in Fig. 8 and 9 respectively. The performance of the said routing protocols with RPGM model for their average actual and predicted path lengths is indicated in Table 7 and Fig. 10.

### *4.3. Analysis the path length on GMK mobility Model*

GMK mobility model shows temporal dependency of velocity between different nodes. The AIC values fort different order $q$ for nodes moving with GMK mobility and following AODV and DSR routing protocol are shown in

Table 5. The AIC values of different $MA(q)$ models in AODV routing and RPGM mobility model

| $MA(q)$ | AIC |
|---|---|
| (1) | 750.0716 |
| (2) | 751.6359 |
| (3) | 734.7796 |
| (4) | 731.7406 |
| **(5)** | **729.8009** |

Table 6. The AIC values of different $MA(q)$ models in DSR routing and RPGM mobility model

| $MA(q)$ | AIC |
|---|---|
| (1) | 371.3798 |
| (2) | 303.9168 |
| (3) | 300.9937 |
| (4) | 280.5821 |
| **(5)** | **280.1460** |

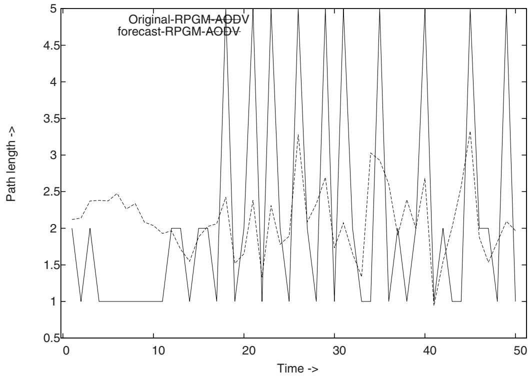


Fig. 8. Time series plot of path length for AODV routing protocol using RPGM Mobility pattern

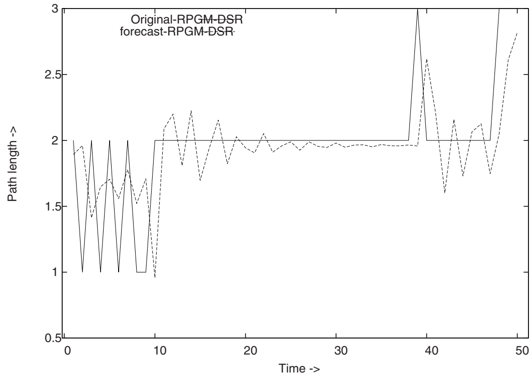


Fig. 9. Time series plot of path length for DSR routing protocol using RPGM Mobility pattern

Table 7. Performance Comparison between different routing protocols using RPGM mobility model

| | Average actual path length | Average predicted path length | Root Mean Squared Error(RMSE) | Mean Absolute Error( MAE) | Mean Absolute % Error(MAPE) |
|---|---|---|---|---|---|
| AODV | 2.1 | 2.04 | 1.3563 | 1.0625 | 65.076 |
| DSR | 1.98 | 2.36 | 0.3817 | 0.25205 | 15.148 |

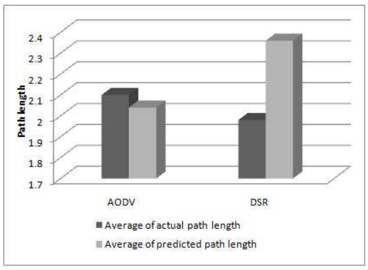


Fig. 10. Comparison between the average actual path length and average predicted path length of different routing protocols in RPGM Mobility pattern

Tables 8 and 9. The order found for AODV protocol is 4 whereas for DSR routing protocol is 5. The ACF and PACF graphs for the said routing protocols are shown in Fig. 11 and 12. The predicted path lengths for the above routing protocols are shown in Fig. 13 and 14. The performance of this model is shown in the Table 10 and the comparison between the average of actual path length and average of forecast path length are depicted in the Fig. 15.

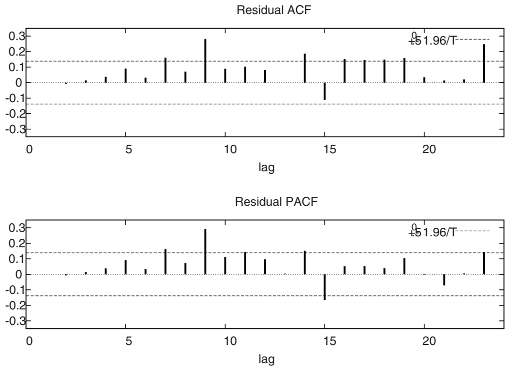


Fig. 11. Autocorrelation function (ACF) and Partial autocorrelation functions (PACF) of path length values for AODV routing protocol using GMK Mobility pattern

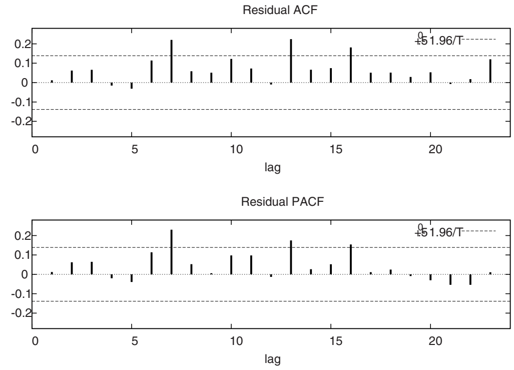


Fig. 12. Autocorrelation function (ACF) and Partial autocorrelation functions (PACF) of path length values for DSR routing protocol using GMK Mobility pattern

Table 8. The AIC values of different $MA(q)$ models in AODV routing and GMK mobility model

| $MA(q)$ | AIC |
|---|---|
| (1) | 1054.769 |
| (2) | 1054.053 |
| (3) | 1038.672 |
| **(4)** | **1034.310** |
| (5) | 1036.294 |

Table 9. The AIC values of different $MA(q)$ models in DSR routing and GMK mobility model

| $ARMA(p, q)$ | AIC |
|---|---|
| (1) | 1015.663 |
| (2) | 1017.608 |
| (3) | 1019.107 |
| (4) | 1010.603 |
| **(5)** | **1008.259** |

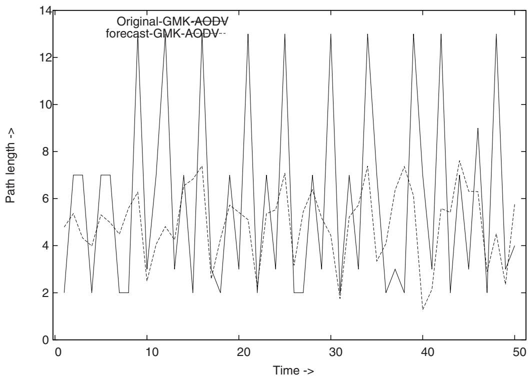


Fig. 13. Time series plot of path length for AODV routing protocol using GMK Mobility pattern

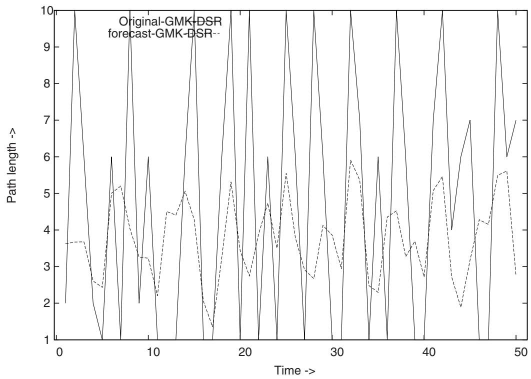


Fig. 14. Time series plot of path length for DSR routing protocol using GMK Mobility pattern

Table 10. Performance Comparison between different routing protocols using GMK mobility model

| | Average actual path length | Average predicted path length | Root Mean Squared Error(RMSE) | Mean Absolute Error( MAE) | Mean Absolute % Error(MAPE) |
|---|---|---|---|---|---|
| AODV | 5.9 | 5.3 | 3.9471 | 3.1507 | 68.4 |
| DSR | 4.78 | 3.2 | 3.4257 | 2.9636 | 118.94 |

## 5. Conclusion

Predicting the path length prediction in MANETs is a challenging issue due to the dynamic features of this kind of networks. We have considered two routing protocols like AODV and DSR and three mobility models such as MHG,

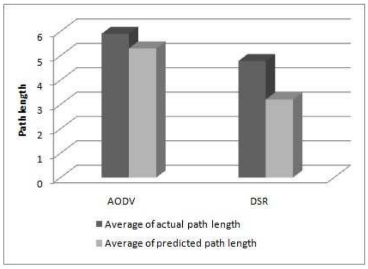


Fig. 15. Comparison between the average actual path length and average predicted path length of different routing protocols in gmk Mobility pattern

RPGM and GMK. We have found experimentally that AODV achieves the shortest path length. In this article, we found that the path length distribution between two nodes are well correlated and are modelled by MA($q$) model for suitable value of $q$. We also evaluated the order of the model and found to lie between 4 and 5 for different routing protocol. Our predicated path length between source-destination nodes in future time frames are found which is close enough to the real values. Our predicted values may help the routing with QoS parameters.

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